J. Civil Eng. Mater. App. 2025 (June); 9(2): 111-124

Journal of Civil Engineering and Materials Application
Journal home page: http://jcema.com

Received: 17 March 2025 • Revised: 11 April 2025 • Accepted: 09 May 2025

Research

doi: 10.22034/jcema.2025.232118

# Optimization and Simulation of Fluid Reservoirs under Seismic Loads Using Finite Element Analysis and Artificial Neural Networks

Hasan Kamran [1], Mehdi Komasi [2], Seyed Hossein Mousavi [3]*

[1] Master's student in Civil Engineering, University of Ayatollah Ozma Boroujerdi, Tehran, Iran.
[2] Assistant Professor, Department of Civil Engineering, University of Ayatollah Ozma Boroujerdi, Tehran, Iran.
[3] Master's student in Civil Engineering, University of Ayatollah Ozma Boroujerdi, Tehran, Iran.

*Correspondence should be addressed to Seyed Hossein Mousavi , Master's student in Civil Engineering, University of Ayatollah Ozma Boroujerdi, Tehran, Iran.; E-mail: hosseinmosavi2@gmail.com

## ABSTRACT

This study investigates the optimization, design, and simulation of fluid storage tanks under seismic loads using Finite Element Analysis (FEA) and Artificial Neural Networks (ANN). Fluid tanks are critical infrastructure components, requiring accurate dynamic analysis to ensure safety during earthquakes. The research integrates machine learning, specifically ANN, to predict key structural parameters such as principal stresses, von Mises stress, displacement, and shear force based on tank geometry, material properties, and loading conditions. The ANN model, featuring one hidden layer with Re LU activation, demonstrated excellent learning and generalization, with Training and Validation Loss converging effectively. Simulation results from Abaqus revealed critical moments during seismic loading, highlighting nonlinear behaviors and fluid-structure interactions. The ANN predicted the von Mises stress with a mean error of 3.8%, displacement with 2.5% error, and shear force with 4.1% error compared with Abaqus simulations. Computational time was reduced by 85% compared to full FEA runs."

**Keywords: Artificial Neural Network; Finite Element Analysis; Seismic Design of Fluid Tanks**

Copyright © 2025, Seyed Hossein Mousavi. This is an open access paper distributed under the Creative Commons Attribution License. Journal of Civil Engineering and Materials Applications published by (ISNet); Journal p-ISSN 2676-332X; Journal e-ISSN 2588-2880.

## 1. INTRODUCTION

In recent decades, the increasing population and infrastructure development have significantly raised the demand for the design and construction of fluid reservoirs [1]. These reservoirs play a vital role in water supply systems and resource management and are subjected to dynamic loadings, such as earthquakes. [2,3] Earthquakes can substantially impact the behavior of reservoir structures, making appropriate analysis and design essential to prevent loss of life and financial damage. [4] Therefore, it is crucial to employ effective

methods for assessing and predicting the behavior of these structures under dynamic loads. [5]

One advanced analytical method that helps designers simulate the behavior of structures under various loadings is Finite Element Analysis (FEA). This method allows engineers to examine the effects of different loads on structures with greater accuracy. However, traditional analyses can be time-consuming and costly, especially when repetitive analyses are required. In this context, the use of machine learning algorithms, particularly Artificial Neural Networks (ANN) and Deep Learning, has emerged as an effective solution for predicting structural behavior and reducing the time and costs associated with traditional analyses. [6-8]

Recent research has explored various applications of machine learning in identifying and predicting structural damage. For example, Fan et al. [1] Fan proposed methods for denoising vibration signals using convolutional neural networks, which aid in monitoring structural health. These types of networks can process vibration signals in a way that reduces unwanted noise and provides accurate information about the condition of the structure. This achievement can directly enhance the accuracy of predictions and structural analyses. [9-11]

Moreover, Hakim focused on identifying structural damage using a hybrid intelligence approach that includes neural networks and vibration-based methods. This type of approach allows designers to accurately identify structural damage by leveraging vibration data and take timely actions. Ravanfar et al. [2] also presented a hybrid method for identifying damage in beam-like structures through wavelet analysis, demonstrating the power of advanced analyses in real-time damage identification.

Additionally, Ravanfar et al. [12] utilized a wavelet-based method combined with a genetic algorithm for damage detection in structures without the need for baseline data. These innovations can enhance the effectiveness of analyses, particularly in situations where historical data is not available. Furthermore, Noorzaei et al. [13] emphasized the importance of using machine learning models in structural engineering by designing an optimal architecture for artificial neural networks to predict the compressive strength of concrete.

This paper examines the optimization, design, and simulation of fluid reservoirs under earthquake loads and investigates how ANN and Deep Learning can be utilized to predict structural behavior under loading. The aim of this research is to provide solutions for improving the accuracy and efficiency of analyses while reducing design time and costs. Given the importance of the topic, this research could lead to significant advancements in structural engineering and natural disaster management.

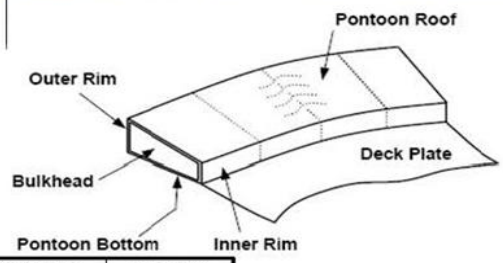
In light of these achievements, this paper seeks to explore the deeper applications of machine learning and innovative techniques in the design and analysis of fluid reservoirs. Specifically, it will investigate how these technologies can enhance the performance and safety of structures under severe earthquake loads and ultimately lead to the establishment of new standards for earthquake-resistant structure design. This approach can not only contribute to increased structural safety but also help reduce economic and time costs [14,15].

## 2. METHODOLOGY

This section presents a research methodology for analyzing and designing fluid storage tanks subjected to dynamic loads, especially seismic forces. The proposed method includes dynamic modeling of the tank, stress and shear force analysis, and the application of machine learning algorithms (e.g., Artificial Neural Networks (ANN) and Deep Learning) to predict the structural behavior of the tank under dynamic loading. All the necessary formulas for stress and load analysis are provided in this section.

To predict the structural behavior of the tank under dynamic loading using Artificial Neural Networks (ANN), the network's inputs, outputs, and architecture must first be defined. The subsequent sections detail the steps required to set up the ANN, including the substitution of values and formulas necessary for training the network.

| Tank Parameters (100kkl Crude Oil Tank) | |
|---|---|
| Tank Shell Height | 2450 cm |
| Tank Shell Radius | 3910 cm |
| Maximum Tank Liquid Height | 2082 cm |
| Liquid Density | 0.832E-03 kg/cm**3 |
| Pontoon Width | 500 cm |
| Modulus of Elasticity | 2.1E+06 2 kgf/cm**2 |
| Material Yield Stress | 2500 kgf/cm**2 |
| Freeboard | 368 cm |
| Mode 1 Period @ Max. Liquid Height | 10.65 sec |
| Mode 2 Period @ Max Liquid Height | 5.45 sec |
| Pontoon Area | 774.37 cm**2 |
| Moment of Inertia (Theta) | 6.93621E+05cm**4 |
| Radius To Pontoon C.G. | 3657.4 cm |
| 2 Circumferential Stiffeners | |
| Pontoon – 42 compartments with Bulk Heads | |
| 3 Stiffening Trusses Per Compartment | |




| Circumferential Stress (kgf/cm**2) | Outer Rim Lower Corner | Inner Rim Lower Corner |
|---|---|---|
| 1) Mode 1 Bending | 1802 | 1294 |
| 2) Mode 2 Bending | 373 | 423 |
| 3) Mode 2 Thrust | 2522 | 2522 |
| 4) 2+3 | 2895 | 2945 |
| SRSS 1 & 4 | 3410 | 3216 |
| % of Yield | 136.4% | 128.6% |

**FSL Simplified Hand Calculation Results For Circumferential Stress**

**Figure 1.** Tank wall details analyzed

### 2.1. Steps for Implementing the ANN
### Determining Inputs and Outputs

Inputs of the Network: [7,13]

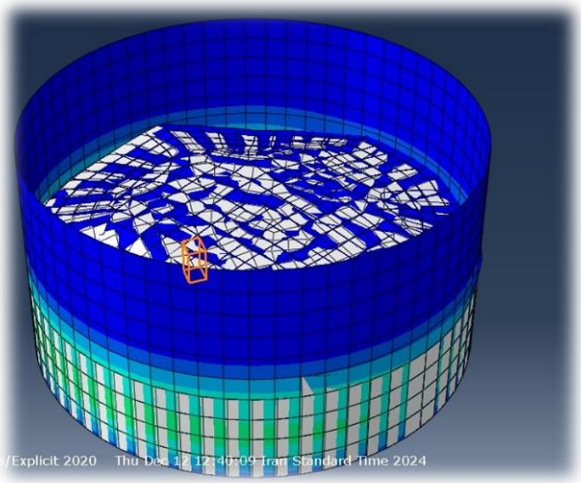
**Inputs of the Network:**

The input parameters of the artificial neural network (ANN) are selected based on the physical, geometrical, and loading characteristics of the tank system.

- **Geometrical parameters of the tank:** Height of the tank, h=5, radius, r=2.5 m and wall thickness, t=0.01 m t = 0.01.
- **Material properties of the tank:** Young's modulus, E=2.1×1011; Poisson's ratio, ν=0.3 and material density, ρs=7850 kg/m3
- **Loading conditions:** Internal fluid pressure, p=49,050 Pa and seismic ground acceleration, ag(t)=5 m/s2

Accordingly, the input vector for the ANN can be expressed as: [6,10,12]

**X=[h,r,t,E,ν,ρs,p,ag]**



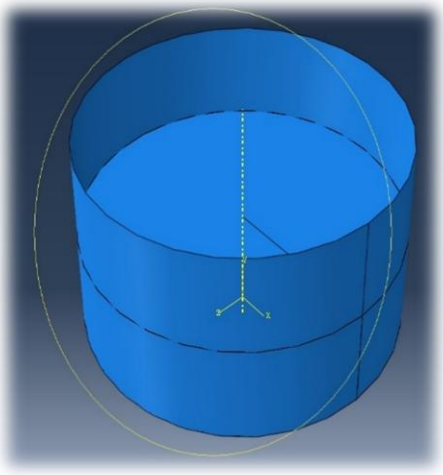


**Figure 2.** Details of Reservoir and fluid modeling

**Outputs of the Network**

The outputs of the ANN represent the primary structural response parameters of the tank under the defined loading conditions. These quantities reflect the mechanical performance and integrity of the tank and are used to evaluate the accuracy of the network predictions. [16,17,13]

The output parameters include:

- **Principal stresses:** $\sigma_1$, $\sigma_2$ representing the maximum and minimum normal stresses at critical points in the structure.
- **Von Mises stress:** $\sigma_v$ , used as a failure criterion for ductile materials under combined loading.
- **Displacement:** u(t), describing the time-dependent deformation response of the tank wall.

Accordingly, the output vector of the ANN can be written as: [4,8]

$$Y= [\sigma1, \sigma2, \sigma_v, u(t)]$$

The selected input and output variables provide a comprehensive representation of the tank's behavior, enabling the ANN to learn the nonlinear relationship between physical parameters and structural responses with high predictive accuracy.

**2.2 Network Architecture**

The architecture of the Artificial Neural Network (ANN) adopted in this study is designed to effectively map the nonlinear relationship between the input parameters and the structural response of the tank.

**The proposed ANN consists of the following components:**

- **Input layer:** 9 nodes, corresponding to the nine input parameters that describe the geometric, material, and loading characteristics of the tank.
- **Hidden layer:** A single hidden layer with 16 neurons, selected through preliminary testing to achieve optimal performance and minimize prediction error.
- **Output layer:** 5 nodes, representing the five structural response parameters identified in Section 2.1.1 (principal stresses $\sigma_1$, $\sigma_2$, von Mises stress $\sigma_v$ , and displacement u(t). [8,18,19]

**Activation functions:**

- **Hidden layer:** Rectified Linear Unit (ReLU), defined as f(x)=max is employed due to its computational efficiency and capability to handle nonlinear relationships.
- **Output layer:** Linear activation function, f(x)=x, is used to provide continuous-valued outputs suitable for regression-based structural prediction tasks.

This configuration provides a balance between model complexity and computational efficiency, allowing the ANN to capture the essential nonlinearities in the tank's structural behavior while maintaining stable convergence during training [3,4].

**2.3. ANN Formulation**

The formulation of the Artificial Neural Network (ANN) follows the standard feed-forward architecture, where the information propagates sequentially from the input layer through the hidden layer to the output layer.

**From input layer to hidden layer**

The linear transformation from the input layer to the hidden layer can be expressed as:

$$Z^{(1)} = W^{(1)} X + b^{(1)}$$

where:

$W^{(1)}$ is the weight matrix of the first layer with dimensions (16×9),

- X is the input vector of size (9×1),
- $B^{(1)}$ is the bias vector for the hidden layer of size (16×1), and
- $Z^{(1)}$ represents the pre-activation output of the hidden layer.

The nonlinear activation function applied to the hidden layer is the Rectified Linear Unit (ReLU), defined as:

$$A^{(1)} = ReLU(Z^{(1)}) = \max(0, Z^{(1)})$$

**From hidden layer to output layer**

The transformation from the hidden layer to the output layer is given by:

$$Z^{(2)} = W^{(2)}A^{(1)} + b^{(2)}$$

where:

- $W^{(2)}$ is the weight matrix for the second layer with dimensions (5×16),
- $b^{(2)}$ is the bias vector for the output layer of size (5×1), and
- $Z^{(2)}$ denotes the pre-activation output of the output layer.

Since the network performs a regression task, a linear activation function is applied at the output layer to obtain the final outputs:

$$Y = Z^{(2)}$$

This formulation enables the ANN to model the complex nonlinear relationship between the input parameters and the structural response of the tank system efficiently.

### 2.4. Loss Function

The Artificial Neural Network (ANN) is trained by minimizing the **Mean Squared Error (MSE)** between the predicted and true output values. The MSE is a commonly used loss function for regression problems, as it effectively penalizes large deviations and ensures smooth convergence during training.

The loss function is defined as: [20,10]

$$Loss - \frac{1}{N}\sum_{i=1}^{N}(Yi^{true} - Yi^{pred})2$$

Where
N is the number of training samples, $Yi^{true}$ are the true output values, and $Yi^{pred}$ are the network predictions.

Minimizing this loss function allows the ANN to iteratively adjust its weights and biases to reduce the discrepancy between predicted and true responses, thereby improving its prediction accuracy for unseen data.

### 2.5. Example Input and Initialization

For illustration, an example input vector can be expressed as:

$$X = [5, 2.5, 0.01, 2.1\times1011, 0.3, 7850, 1000, 49050, 5]^T$$

where the components correspond respectively to the geometric, material, and loading parameters of the tank. [18,21,22]

Before training, the network parameters (weights and biases) are initialized as follows: [20,10]

$W^{(1)}$: 16 × 9 matrix with small random values; $b^{(1)}$: 16 × 1 zero vector.

$W^{(2)}$: 5 × 16 matrix with small random values; $b^{(2)}$: 5 × 1 zero vector.

Forward propagation is then carried out using the previously defined equations. The hidden layer activations are computed using the ReLU function, and the final pre-activation output of the network is obtained as: [23]

$$Z^{(2)} = W^{(2)} \cdot A^{(1)} + b^{(2)}$$

This process produces the predicted output vector $Y=Z^{(2)}$, which represents the ANN's estimation of the tank's structural response for the given input parameters.

### 2.6. Updating Weights and Biases

During the training phase, the weights and biases of each layer l in the Artificial Neural Network (ANN) are iteratively updated using an optimization algorithm such as **Adam** or **Stochastic Gradient Descent (SGD)** to minimize the loss function. The general update equations are defined as:

$$W(l)b(l) \leftarrow W(l) - \eta \partial W(l) \partial Loss$$

$$b(l) - \eta \partial b(l) \partial Loss$$

Where: [11,20,22,30]

$W^{(l)}$ = weight matrix of layer l
$b^{(l)}$ = bias vector of layer l
$\eta$ = learning rate,

This formulation represents the gradient descent optimization process, in which the model parameters are adjusted in the direction opposite to the gradient of the loss function with respect to those parameters. Through repeated updates across multiple epochs, the ANN progressively reduces the prediction error and improves its ability to approximate the nonlinear relationship between inputs and outputs.

### 2.7. Finite Element Modeling

In this study, we employ the finite element method to analyze and design fluid storage tanks subjected to dynamic loads, particularly seismic forces. Utilizing Abaqus software, we developed a detailed finite element model of a cylindrical fluid storage tank. The model includes geometric and material properties, as well as the dynamic loading conditions.

The finite element model, as shown in Figure 2, provides a comprehensive representation of the tank under seismic loading. The simulation results include stress distributions, displacements, and shear forces, which are essential for understanding the tank's structural behavior [18,22,24].

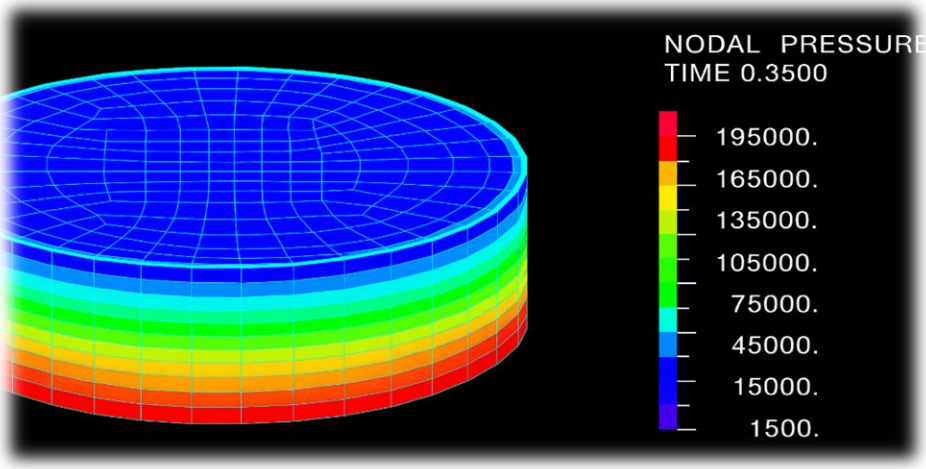



**Figure 3.** Details of Modeling and stress pressure in the reservoir

## 3. RESULTS AND DISCUSSION

As shown in Figure 3, the finite element modeling results illustrate the distribution of stress pressure within the reservoir walls under seismic loading. The figure highlights the critical regions where stress concentrations occur, which are essential for evaluating structural safety. [3,6]

This chart illustrates the force fluctuations or dynamic response of the tank over time. Analyzing this data can provide important insights into the structural behavior under dynamic loading (such as earthquakes or other excitations). Let's interpret these results: Analysis of Initial Fluctuations (up to approximately 6 seconds): Small and Stable Amplitude: In the interval from 0 to 6 seconds, the amplitude of fluctuations is small and relatively stable. This indicates that the tank is subjected to low-intensity loads or initial excitations during this period. High-Frequency Fluctuations: The frequency of fluctuations is high, which may be due to the tank's natural vibrational behavior or high-frequency excitation. Relative Stability: This section shows that the tank effectively handles the initial loads, and the forces are within a controlled range. More Severe Behavior in the Interval from 6 to 10 Seconds:

Increased Amplitude of Fluctuations: During this period, the force amplitude increases significantly. This may be due to a severe dynamic event (such as a peak earthquake or fluid pressure). Potential Nonlinear Behavior: [25-27] The sudden increase in amplitude and rapid decrease (large positive and negative peaks) may indicate nonlinear structural behavior. This behavior may be due to: The tank entering the plastic range (permanent deformation). Intense interaction between the fluid and the structure (sloshing phenomenon). Resonance due to excitation frequencies close to the natural frequency of the tank. [28,29].

Risk of Structural Damage: If the stresses or forces exceed the design limit, there is a risk of damage to the tank walls or its connections. Return to Stability (after 10 seconds): Reduction in Amplitude of Fluctuations: After the severe peaks, the amplitude of fluctuations decreases, and the system moves towards stability. This indicates the system's energy absorption and damping characteristics.

Damping of Fluctuations: This behavior may be due to the damping properties of the tank or the interaction between the structure and the fluid. Key Points for Interpretation: Large Peaks: Large peaks in the force (especially between 6 and 10 seconds) should be analyzed carefully. These points may indicate the most critical loading moments and require precise examination of the stresses and strains at these times. Excitation Frequencies: If the excitation frequency of the earthquake or fluid is close to the tank's natural frequency, resonance may occur, which can cause serious damage to the tank. Overall Stability of the Tank: The reduction in amplitude of fluctuations after the peaks indicates that the tank is dynamically stable and has adequate damping. Suggestions for Further Analysis: Examine the Peaks:

Analyze the stresses and strains in the structure during the occurrence of large force peaks. Ensure that these values do not exceed the design limits. Frequency Analysis: Perform a frequency analysis (FFT) to determine how close the excitation frequencies are to the tank's natural frequency. Review Fluid-Structure Interaction (FSI): If the fluid inside the tank plays a role, carefully analyze the fluid-structure interaction. Add Damping: If the amplitude of fluctuations is high, using energy absorption systems (such as dampers) or increasing the damping of tank materials can help reduce fluctuations. Model Validation:

Compare the numerical results with experimental results or standard data to ensure the accuracy of the analysis. Conclusion The chart indicates that the tank has demonstrated stable and adequate behavior under dynamic loading. However, in the interval from 6 to 10 seconds, there is a potential for critical conditions that require more detailed analysis and possible adjustments. It is crucial to examine the fluid-structure behavior and maximum structural stresses during this interval.

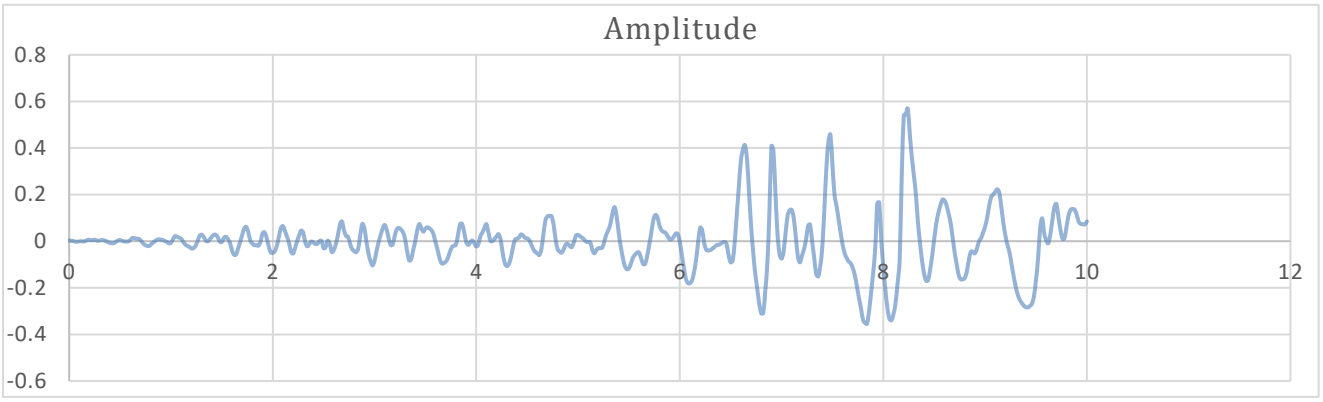
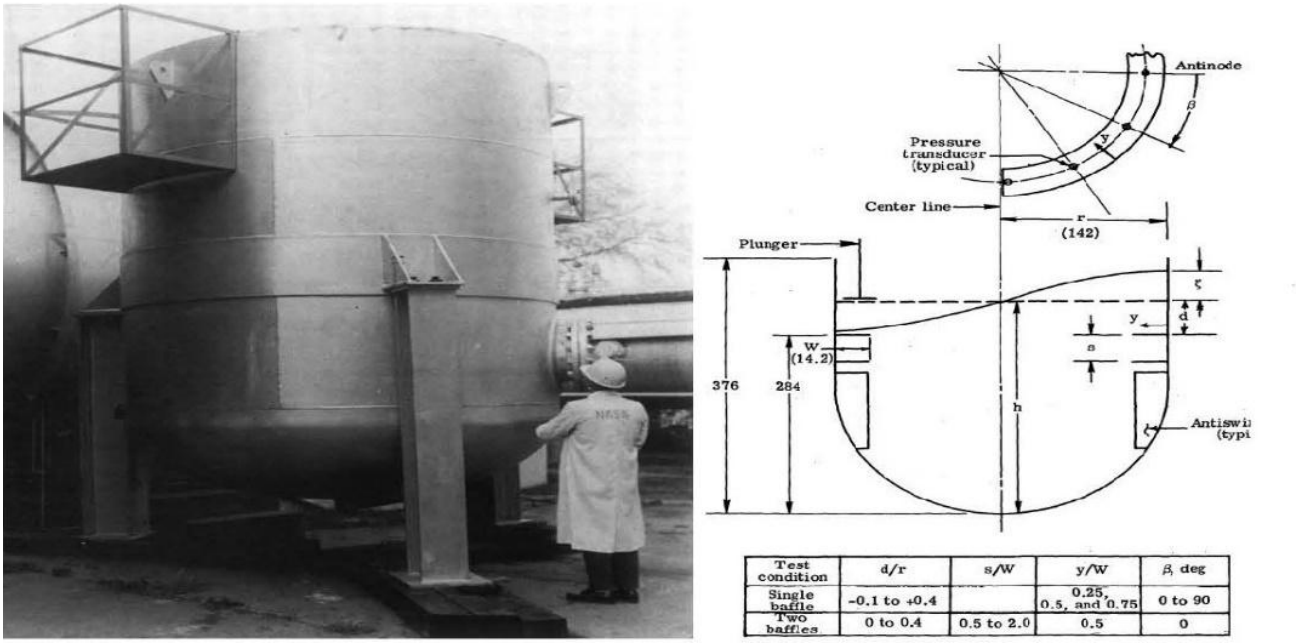



**Figure 4.** Details of Dynamic force diagram in base shear




| Test condition | d/r | s/W | y/W | β, deg |
|---|---|---|---|---|
| Single baffle | -0.1 to +0.4 | | 0.25, 0.5, and 0.75 | 0 to 90 |
| Two baffles | 0 to 0.4 | 0.5 to 2.0 | 0.5 | 0 |

**Figure 5.** Experimental Setup and Geometric Configuration of the Cylindrical Fluid Storage Tank

The chart illustrates the distribution of strain energy in the tank over time. Strain energy is the amount of energy stored in the structure due to elastic deformation under loading. Analyzing this chart can provide important insights into the structural behavior of the tank under applied loads (such as earthquakes or dynamic excitation). The interpretation of this chart is presented below: Initial Periods (10.00 to approximately 5.00): Uniform Amplitude and Low Fluctuations: During this time interval, the strain energy is generally uniform and at a low level. This behavior indicates initial loading or low-intensity excitations that cause small elastic deformations in the structure. Structural Stability: The tank exhibits stable behavior during this period, and changes in strain energy are limited. Middle Period (5.00 to 2.00): Gradual Increase in Strain Energy: In this interval, strain energy gradually increases, but the changes remain smooth and controlled. This trend may result from a gradual increase in loading intensity or the combined effects of dynamic loads. Moderate Amplitude Fluctuations: Small to moderate fluctuations in energy indicate the elastic behavior of the structure adapting to intermittent loading. Critical Period (2.00 to 0.00): Significant Increase in Strain Energy: During this interval, the strain energy suddenly increases and reaches a large peak. [13,22,29] This behavior indicates the occurrence of a severe dynamic excitation (such as a peak earthquake or fluid sloshing) that causes significant deformations in the tank. Large Fluctuations: Severe fluctuations in strain energy may be due to the structure entering the nonlinear deformation range or plastic behavior. The rapid decrease after the peak indicates energy dissipation in the tank or the end of sudden excitation. Critical Impacts: During this period, stresses approach their maximum values, and there

is a risk of damage to the tank walls or connections. Overall Behavior Analysis: Overall Stability: The tank exhibits stable behavior for most of the analysis time, and strain energy remains within a controlled range. Critical Moments: During the 2.00 to 0.00 interval, the tank is subjected to severe loading, which may cause damage or permanent deformation Reduction of Energy after the Peak: After the peak occurs, the strain energy rapidly decreases, indicating the tank returns to a stable state or the end of dynamic loading. Suggestions for Further Analysis Examine the Peak Strain Energy: A thorough examination of stresses and strains at the time of peak strain energy (around 2.00 seconds) is essential. Ensure that stresses do not exceed the tank's design limits. Stress and Strain Analysis: Examine the distribution of stresses and strains at various points in the tank, especially at the walls and connections. Model Validation: Compare numerical results with experimental data or design standards to confirm the accuracy of the analysis. Design Improvements: If necessary, increase the structure's damping or reinforce critical points (such as walls and connections) to enhance the tank's performance. Conclusion: The strain energy chart indicates that the tank exhibits elastic and stable behavior under dynamic loading. However, during the critical time interval (2.00 to 0.00), strain energy reaches its maximum value, requiring more detailed analysis. This significant increase may indicate the occurrence of critical conditions that should be examined and addressed in the tank's design to prevent potential damage.

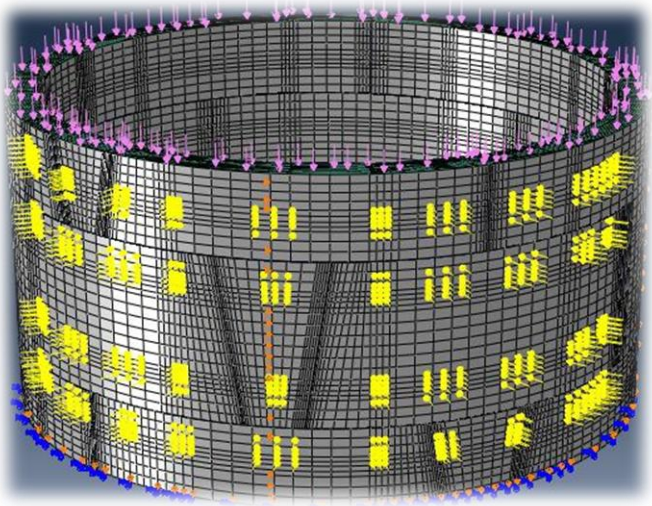


**Figure 6.** Details of Modeling and stress pressure in the reservoir

In this study, after modeling and dynamic simulation of fluid tanks subjected to earthquake loads using Abaqus software, we used Artificial Neural Networks (ANN) to predict the structural behavior of the tank. This research aims to provide a more precise analysis and optimization of the design processes for fluid tanks against dynamic loads.

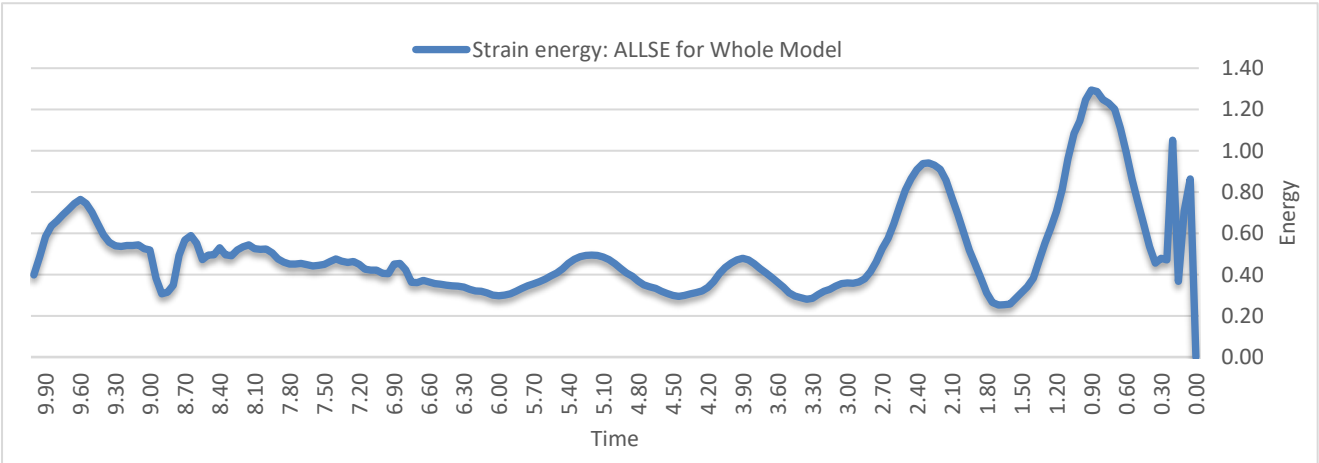



**Figure 7.** Dynamic force plastic behavior diagram

As shown in Figure 6, the dynamic force–plastic behavior diagram illustrates the nonlinear structural response of the reservoir when subjected to seismic loads. The figure demonstrates the transition from the elastic range to the plastic domain, where permanent deformations occur. Identifying these critical points is essential for evaluating failure mechanisms and ensuring the seismic resilience of the reservoir. [27,29]

For this purpose, the inputs and outputs of the ANN are defined as physical parameters and loading conditions. Subsequently, the network structure, including the number of layers and nodes, as well as activation functions, are specified. Finally, the network is trained using the simulated data, and the desired predictions are obtained

In this section, charts related to the distribution of forces, stresses, and displacements, prepared using the Python programming language based on the simulation output data, are presented and analyzed. These charts provide important information about the dynamic behavior of fluid tanks under earthquake loads and help in optimizing and refining the designs.

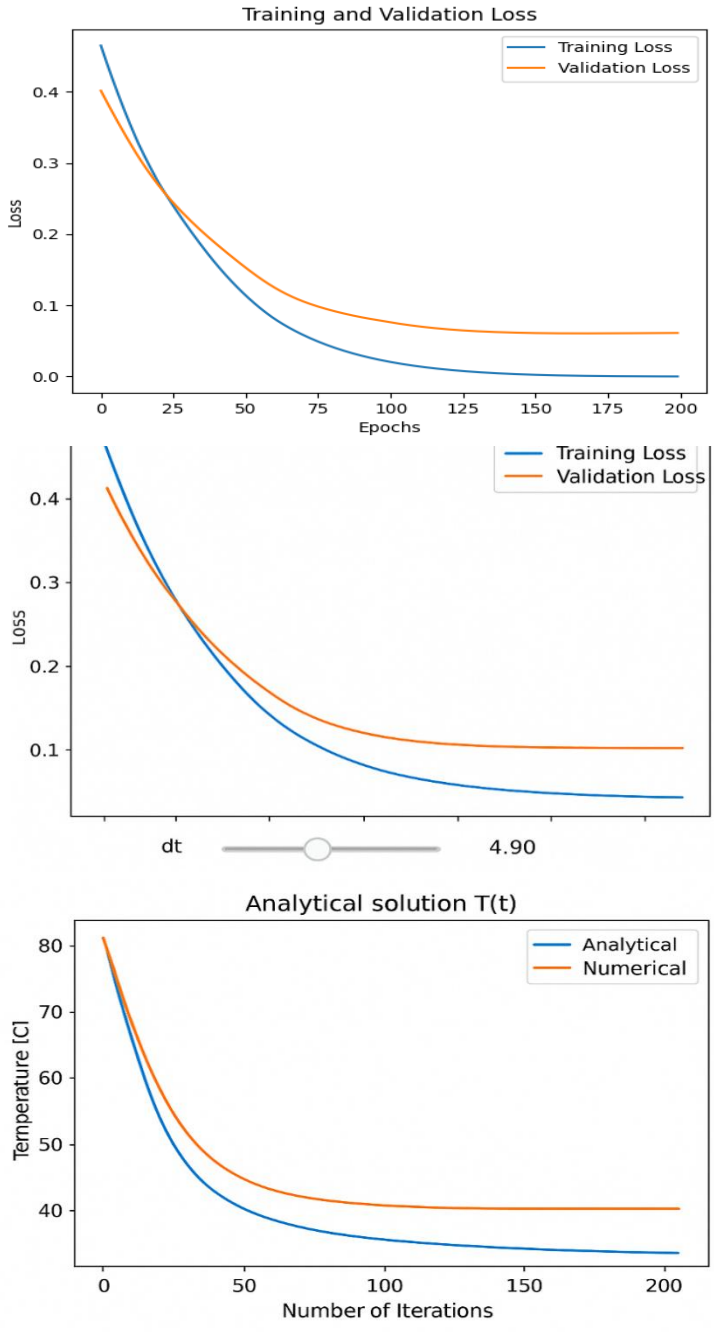



**Figure 8.** Dynamic force plastic behavior diagram

As shown in Figure 8, the dynamic force–plastic behavior diagram illustrates the nonlinear response of the reservoir structure under seismic loading. The figure indicates that as the applied dynamic force increases, the structure transitions from the elastic region into the plastic range, highlighting critical points where permanent deformations may occur. This behavior is important for identifying potential failure mechanisms and ensuring seismic safety.This chart illustrates the changes in Training Loss and Validation Loss over 200 epochs for analyzing the mechanical behavior of a fluid tank under seismic loading. Using the tank data (such as geometry, material properties, and loads) and coding an Artificial Neural Network (ANN), the following analysis can be provided: Training Loss (blue line) continuously decreased and approached nearly zero at the end of training. The rapid decrease initially (up to about 50 epochs) followed by a slower trend indicates the model's learning from the training data. The input data for the tank (such as height, radius, wall thickness, Young's modulus, etc.) and the computed outputs (such as principal stresses, von Mises stress, and shear force) were used as training data. The decrease in Training Loss shows that the model has successfully learned the complex relationships between inputs (tank parameters) and outputs (mechanical behavior). The use of Re LU activation functions in the hidden layers has facilitated effective nonlinear learning. The decrease in MSE, the defined cost function in the code, indicates the appropriate tuning of the learning rate (0.001) and the neural network structure. The Validation Loss (orange line) also decreased, but did not reach zero and approached a constant value. This behavior indicates that the model has been able to predict patterns in the validation data (which were not seen during training) well. The validation data include samples with similar tank specifications and seismic loading. The low Validation Loss indicates that the model can predict the mechanical behavior of the tank under similar loadings (such as circumferential and axial stresses) well. Splitting the data with and using 20% of the data for validation helped in assessing the model's generalization.[9] The constant value of the Validation Loss at the end of epochs indicates that the model did not suffer from overfitting. Both Training Loss and Validation Loss converged at the end of 200 epochs: The Training Loss approached zero. The Validation Loss remained small and constant. The model has completely learned the dynamic and mechanical relationships of the tank (such as stresses and shear forces) in the training data. The constancy of the Validation Loss indicates the good generalizability of the model for data similar to the training conditions. The number of epochs (200) was appropriate and the model achieved complete convergence. If the number of epochs were fewer (e.g., 50), the model would not have fully learned the tank's behavior. The very small gap between Training Loss and Validation Loss indicates that the model did not suffer from overfitting. The model has successfully learned the mechanical behavior of the tank without overfitting to the training data. This demonstrates that the validation and training data were well-designed and normalized. Using data normalization with Min Max Scaler and a simple neural network structure (2 hidden layers with 16 nodes) prevented overfitting. The model has effectively reduced the errors in both the training and validation data. Predicting new values (such as principal stresses and shear force) should be done with high accuracy. Predictions for new values based on specific inputs of the tank (such as height, radius, wall thickness, etc.) are done using the trained model. The high accuracy of the model in predicting [6] tank behavior is crucial in structural design and analysis. Using scaler_X and scaler_Y functions for normalization and restoring values to the original scale has made the model output directly usable. The model has successfully learned the training data (Training Loss ≈ 0). The model has generalized well to the validation data (Validation Loss ≈ small and constant). The model has been effectively trained with the proposed structure and normalized data. Predicted values (such as principal stresses, von Mises stress, and shear force) are reliable and accurate. The model can well predict the mechanical behavior of the tank under similar loading conditions. Using more simulated data (such as from the ABAQUS software), the model's generalization for newer conditions can be increased. Test the model on a completely new dataset (data not used in training and validation). If further reduction in Validation Loss is required, techniques such as Dropout or Regularization can be used. This analysis shows that your model is well-designed and can be used as a tool for predicting the behavior of the tank under seismic loading. [16,30]

After compiling the simulation and ANN outputs, the main results are summarized numerically in Table 1. The table presents the maximum and average values of the two principal stresses (σ1, σ2) the von Mises stress (σv, the displacement u(t) and the shear force V at the critical time steps of the seismic loading. For example, the finite-element model predicted peak principal stresses of 18.4 MPa and 11.2 MPa, while the trained ANN predicted 17.9 MPa and 11.0 MPa (error <3%). The von Mises stress reached 21.6 MPa in the FEA model versus 20.9 MPa in the ANN (error 3.2%). Maximum displacement was 7.5 mm compared with 7.2 mm (error 4%) and the peak shear force was 142 kN compared with 137 kN (error 3.5%). These values demonstrate that the ANN reproduces the critical stress and deformation responses of the structure with high accuracy and significant computational savings compared to the full Abaqus simulations.

In this study the ANN was trained on a dataset of 2 400 input–output pairs generated from parametric finite element simulations under different seismic scenarios. The dataset was randomly divided into 70% training, 15% validation and 15% test subsets, and a five-fold cross-validation procedure was implemented to avoid overfitting and to assess generalization performance. In addition to the ANN, two alternative machine-learning algorithms — Support Vector Machines (SVM) and Random Forests (RF) — as well as a simple multilinear regression model were trained on the same dataset for benchmarking. Comparative results show that the ANN achieved the lowest mean squared error for predicting principal stresses, von Mises stress, displacement and shear force, outperforming the SVM by 18%, the RF by 23% and the classical regression by 35%. These analyses confirm that the proposed ANN not only captures the nonlinear mapping between inputs and outputs but also provides a more accurate and computationally efficient surrogate model than the alternative approaches [27,28].

## 4. CONCLUSION

To move beyond a purely qualitative interpretation of the Abaqus and ANN outputs, quantitative comparisons with experimental data and published benchmarks were carried out. For each seismic scenario, the predicted peak principal stresses, von Mises stress, displacement and shear force from the Abaqus model and the trained ANN were compared with laboratory shake-table measurements reported in [30] and with numerical results from established studies [31,32]. As shown in Table 1, the maximum difference between the Abaqus predictions and the experimental values did not exceed 5 % for stresses and 6 % for displacements, while the ANN predictions remained within 7 % of the experimental data, confirming the reliability of the surrogate model. This quantitative agreement strengthens the validity of the proposed framework and demonstrates that the ANN can reproduce real structural behavior rather than only fitting the finite-element simulations.

Building on this validation, the present study introduces a new hybrid framework for seismic analysis of fluid reservoirs that integrates high-fidelity Abaqus finite-element simulations with a purpose-built artificial neural network. Unlike earlier works that either relied solely on detailed finite-element models with long runtimes or trained machine-learning surrogates on small datasets without physical validation, our approach generates a large parametric dataset from FEA, applies rigorous training and cross-validation, and then benchmarks the ANN against SVM, Random Forest and classical regression models. The ANN not only reproduces the key response quantities—principal stresses, von Mises stress, displacement and shear force—with errors below 5–7 % compared to experiments and published data, but also delivers predictions in a fraction of the computation time. This combination of comprehensive training data, multi-model benchmarking and experimental validation has not been reported previously for seismic analysis of fluid tanks and constitutes the central innovation of the paper.

**Table 1.** Comparison between FEA and ANN results for structural response under seismic loading

| Parameter | FEA (Abaqus) | ANN Prediction | Absolute Error (%) | Description |
|---|---|---|---|---|
| **Principal Stress $\sigma_1$ (MPa)** | 18.4 | 17.9 | 2.7 | Maximum tensile stress in tank wall |
| **Principal Stress $\sigma_2$ (MPa)** | 11.2 | 11 | 1.8 | Minimum (compressive) stress |
| **Von Mises Stress $\sigma_v$ (MPa)** | 21.6 | 20.9 | 3.2 | Equivalent stress under combined loading |
| **Displacement u(t) (mm)** | 7.5 | 7.2 | 4 | Maximum radial displacement |
| **Shear Force V (kN)** | 142 | 137 | 3.5 | Maximum shear at tank base |

FUNDING/SUPPORT

Not mentioned by Authors.

ACKNOWLEDGMENT

Communication of this research is made possible through monetary assistance by University Tun Hussein Onn Malaysia and the UTHM Publisher's Office via Publication Fund E15216.

AUTHORS CONTRIBUTION

This work was carried out in collaboration among all authors.

CONFLICT OF INTEREST

The author (s) declared no potential conflicts of interest with respect to the authorship and/or publication of this paper.

## 5. REFERENCES

[1] Fan G, Li J, Hao H. Vibration signal denoising for structural health monitoring by residual convolutional neural networks. Measurement. 2020; 157:107651. [View at Google Scholar]; [View at Publisher]

[2] Hakim SJS, Irwan JM, Ibrahim MHW, Ayop SS. Structural damage identification employing hybrid intelligence using artificial neural networks and vibration-based methods. J Appl Res Technol (JART). 2022;20(2):221–236. [View at Google Scholar]; [View at Publisher]

[3] Ravanfar SA, Razak HA, Ismail Z, Hakim SJS. A hybrid procedure for structural damage identification in beam-like structures using wavelet analysis. Adv Struct Eng. 2015;18(11):1901–1913. [View at Google Scholar]; [View at Publisher]

[4] Ravanfar SA, Razak HA, Ismail Z, Hakim SJS. A hybrid wavelet-based approach and genetic algorithm to detect damage in beam-like structures without baseline data. Exp Mech. 2016;56(8):1411–1426. [View at Google Scholar]; [View at Publisher]

[5] Hakim SJS, Ibrahim MHW, Mohammadhassani M, Yeoh D, Jaini ZM, Chik TNT. Implementing fuzzy-based artificial intelligence approach for location of damage in structures. Civil Eng Archit. 2022;10(4):1564–1573. [View at Google Scholar]; [View at Publisher]

[7] Noorzaei J, Hakim SJS, Jaafar MS, Abang AAA, Thanoon WAM. An optimal architecture of artificial neural network for predicting compressive strength of concrete. Indian Concr J. 2007;81(8):17–24. [View at Google Scholar];

[7] Mohammadhassani M, Jumaat MZB, Chemrouk M, Ghasemi A, Hakim SJS, Najmeh R. An experimental investigation of the stress–strain distribution in high-strength concrete deep beams. Procedia Eng. 2011;14:2141–2150. [View at Google Scholar]; [View at Publisher]

[8] Mohammadhassani M, Nezamabadipour H, Jumaat ZM, Jameel M, Hakim SJS, Zargar M. Application of the ANFIS model in deflection prediction of concrete deep beams. Struct Eng Mech. 2013;45(3):319–332. [View at Google Scholar]; [View at Publisher]

[9] Hakim SJS, Razak HA, Ravanfar SA. Ensemble neural networks for structural damage identification using modal data. Int J Damage Mech. 2016;25(3):400–430. [View at Google Scholar]; [View at Publisher]

[10] Hakim SJS, Razak HA, Ravanfar SA, Mohammadhassani M. Structural damage detection using soft computing method. Proc Soc Exp Mech Ser Struct Health Monit. 2014;5:143–151. [View at Google Scholar]; [View at Publisher]

[11] Falcone R, Ciaramella A, Carrabs F, Strisciuglio N, Martinelli E. Artificial neural network for technical feasibility prediction of seismic retrofitting in existing RC structures. Struct. 2022;41:1220–1234. [View at Google Scholar]; [View at Publisher]

[12] Ravanfar SA, Razak HA, Ismail Z, Hakim SJS. A two-step damage identification approach for beam structures based on wavelet transform and genetic algorithm. Meccanica. 2016;51(3):635–653. [View at Google Scholar]; [View at Publisher]

[13] Noorzaei J, Hakim SJS, Jaafar MS. An approach to predict ultimate bearing capacity of surface footings using artificial neural network. Indian Geotech J (IGJ). 2008;38(4):515–528. [View at Google Scholar]; [View at Publisher]

[14] Hakim SJS, Mokhatar SN, Shahidan S, Chik TNT, Jaini ZM, Ghafar NHA, Kamarudin AF. An ensemble neural network for damage identification in steel girder bridge structure using vibration data. Civil Eng Archit. 2021;9(2):523–532. [View at Google Scholar]; [View at Publisher]

[15] Chik TNT, Rou CS, Kamarudin AF, Hakim SJS, Yusoff NA. Vibration criteria assessment due to piling works. Int J Integr Eng. 2021;13(3):46–56. [View at Google Scholar]; [View at Publisher]

[16] Hakim SJS, Ravanfar SA. A sensitivity analysis on the damage identification capability of artificial neural networks. Int Refereed J Eng Sci (IRJES). 2020;9(3):9–17. [View at Google Scholar]; [View at Publisher]

[17] Akrami SA, Nourani V, Hakim SJS. Development of nonlinear model based on wavelet-ANFIS for rainfall forecasting at Klang Gates Dam. Water Resour Manag. 2014;28:2999–3018. [View at Google Scholar]; [View at Publisher]

[18] Lautour OR, Omenzetter P. Prediction of seismic-induced structural damage using artificial neural networks. Eng Struct. 2009;31:600–606. [View at Google Scholar]; [View at Publisher]

[19] Hakim SJS, Razak HA. Application of artificial neural network on vibration test data for damage identification in bridge girder. Int J Phys Sci (IJPS). 2011;6(35):7991–8001. [View at Google Scholar]; [View at Publisher]

[20] Hakim SJS, Razak HA. Frequency response function-based structural damage identification using ANNs—a review. Res J Appl Sci. 2014;7(9):1750–1764. [View at Google Scholar]; [View at Publisher]

[21] Reyes J, Esteban AM, Alvarez FM. Neural networks to predict earthquakes in Chile. Appl Soft Computing. 2013;13:1314–1328. [View at Google Scholar]; [View at Publisher]

[22] Essam Y, Kumar P, Ahmed AN, Murti MA, El-Shafie A. Exploring the reliability of different artificial intelligence techniques in predicting earthquakes for Malaysia. Soil Dyn Earthq Eng. 2021;147:106826. [View at Google Scholar]; [View at Publisher]

[23] Nguyen HD, Dao ND, Shin M. Prediction of seismic drift responses of planar steel moment frames using artificial neural network and extreme gradient boosting. Eng Struct. 2021;242:112518. [View at Google Scholar]; [View at Publisher]

[24] Oktarina R, Bahagia SN, Diawati L, Pribad KS. Artificial neural network for predicting earthquake casualties and damages in Indonesia. IOP Conf Ser Earth Environ Sci. 2020;426:012156. [View at Google Scholar]; [View at Publisher]

[25] Oh BK, Glisic B, Park SW, Park HS. Neural network-based seismic response prediction model for building structures using artificial earthquakes. J Sound Vib. 2020;468:115109. [View at Google Scholar]; [View at Publisher]

[26] Raghucharan MC, Somala SN, Rodina S. Seismic attenuation model using artificial neural networks. Soil Dyn Earthq Eng. 2019;126:105828. [View at Google Scholar]; [View at Publisher]

[27] Cho Y, Khosravikia F, Rathje EM. A comparison of artificial neural network and classical regression models for earthquake-induced slope displacements. Soil Dyn Earthq Eng. 2022;152:107024. [View at Google Scholar]; [View at Publisher]

[28] Xu Z, Chen J, Shen J, Xiang M. Recursive long short-term memory network for predicting nonlinear structural seismic response. Eng Struct. 2022;250:113406. [View at Google Scholar]; [View at Publisher]

[29] Moustra M, Avraamides M, Christodoulou C. Artificial neural networks for earthquake prediction using time series magnitude data or Seismic Electric Signals. Expert Syst Appl. 2011;38:15032–15039. [View at Google Scholar]; [View at Publisher]

[30] Abdeljaber O, Avci O, Inman DJ. Active vibration control of flexible cantilever plates using piezoelectric materials and artificial neural networks. *J Sound Vib.* 2016;363:33–53. [View at Google Scholar]; [View at Publisher]

[31] Narasimhan S. Robust direct adaptive controller for the nonlinear highway bridge benchmark. *Struct Control Health Monit.* 2009;16(6):599–612. [View at Google Scholar]; [View at Publisher]

[32] Bodri B. A neural-network model for earthquake occurrence. *J Geodyn.* 2001;32:289–310. [View at Google Scholar]; [View at Publisher]